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Artificial Neural Network (ANN) Modeling for Estimating the Glycemic Index of Traditional Ivorian Food

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Abstract

The glycemic index (GI) is a qualitative indicator of the glycemic response of a carbohydrate food. Its variability is due to the composition of the food, which in turn is related to the technology applied to it. This study describes a data processing analysis method that allows the GI of food to be accurately predicted using a model. Data from the food composition table, combined with information from the table of GI values of foods, are processed using an artificial neural network (ANN) to produce a predicted value for the GI of the food. For the samples studied (n = 30), consisting of a variety of traditional dishes (base component ± accompanying sauce), $r^2 = 0.968$, and the learning root mean square error analysis (learning RMSE) tends towards 0. The 7-9-1 neural structure (7 neurons in the input layer, 9 neurons in the hidden layer, and 1 neuron in the output layer) is the most appropriate neural model. During the test phase, it showed the highest R^2, indicating a good predictive ability for the ANN method. These results suggest that the selected ANN has a good capacity to respond satisfactorily to an input that is not part of the data from the learning phase. This method, which is fast and inexpensive, compared to *in vivo* tests, is a valuable tool for predicting the GI of Ivorian traditional foods more effectively.

Keywords

Glycemic Index, Modelling, Recurrent Multilayer Perceptron, Mixed Meals

1. Introduction

The glycemic index (GI) is now widely used around the world to manage blood sugar levels in patients with diabetes and other related disorders [1]. It is a physiological indicator used to differentiate between carbohydrate-containing foods based on the increase in postprandial blood glucose levels [2]. In Côte d'Ivoire, the nutritional approach to the resurgence of diabetes mellitus has led to the development of a table of glycemic index values for traditional dishes. Some thirty dishes based on rice, manioc, yam, maize, and plantain were studied. The main idea was to guide diabetics and people in good health in their dietary choices towards foods with a low or medium GI [3]. The glycemic index values of traditional dishes are of considerable importance for the prevention and treatment of diabetes in general, and for improving the scientific skills of professionals dealing with diabetes mellitus (doctors, nurses, dieticians, nutritionists).

For a certain food, the GI is the result of complex metabolic phenomena, which must be considered in nutritional choices and advice, especially in a context where most of the meals consumed in Côte d'Ivoire are mixed meals. Several factors likely to modify the GI of a food have been widely demonstrated in the scientific literature [4]. These factors are biochemical composition (starch, amylose, and amylopectin content, type of sugar, fiber, lipids, proteins, organic acids, anti-nutritional factors), starch structure (grain size and dispersion) and physico-chemical constraints such as degree of hydration, temperature, pressure and cooking time. Some of these components are considered minor, while others are much more important [4].

In current nutritional and dietetic practice, most of the advice given during consultations does not take into consideration these factors of variation in GI, which are reflected in the physiological behavior of the nutrients contained in foods. Consequently, understanding these factors would provide a better understanding of the GI of a given food, particularly for mixed meals, i.e. meals consisting of a base and a side dish. It would also make easier and cheaper to anticipate the potential impact of these foods on health, using mathematical models. The use of modeling as a means of explaining and predicting GI is not new [5]-[7]. This is notably the case in the work of Iancu *et al.* [8] and Pérez-Gandía *et al.* [9], where artificial neural networks (ANNs) were used as a modeling tool to predict blood glucose levels in an automatic insulin pump control system. The glycemic index of a food ration can also be estimated using the Food and Agriculture Organization (FAO) prediction model [10]. In contrast to this basic model, the artificial neural network is capable of making intelligent decisions without human intervention. In fact, they can learn and represent relationships between input and output data that are non-linear and complex. This work aims to develop a neural architecture for predicting the glycemic index of composite meals (basic component with or without accompanying sauce) based on the use of a multi-layer gradient back propagation neural network.

2. Materials and Methods

2.1. Food Products

Thirty (30) dishes from Ivorian traditional recipes have been characterized using standard analytical methods [11]. These foods are plantain-derived products (Plantain and plantain-derived products), products derived from some cereals (Cereals and cereal-derived products), and foods based on roots and tubers (Roots, tubers, and tuber-derived products). This table includes both foods with and without accompanying sauces. The technologies used to prepare and cook these foods have been described in several previous studies [12]-[18]. All values were presented for an edible 100 g portion of these foods. The nutritional composition and GI values of these foods are summarized in **Table 1**.

Table 1. Nutrient (/100 g dry matter) and GI values of traditional Ivorian food used in this study.

N°	Foods	Protein (g)	Lipids (g)	Available CHO* (g)	Total dietary fiber (g)	Ash (g)	GI	Ref.
	Plantain banana and by-products							
1	Fried plantain (aloco aag6)	4.4 ± 0.0	11.6 ± 0.1	82.6 ± 0.1	1.6 ± 0.0	1.5 ± 0.0	39 ± 1	[12]
2	Fried plantain (aloco aag7)	8.8 ± 0.1	12.4 ± 0.1	78 ± 0.0	1.6 ± 0.0	1.6 ± 0.1	38 ± 0	[12]
3	Charcoal-roasted plantain (raf2)	5.3 ± 0.1	0.3 ± 0.10	93.1 ± 0.1	1.7 ± 0.1	1.4 ± 0.0	89 ± 1	[12]
4	Plantain chips (chips cam1)	5.3 ± 0.1	10.9 ± 0.1	81.9 ± 0.1	1.7 ± 0.1	2.0 ± 0.1	45 ± 0	[12]
5	Plantain fritters (Klaclo kam8)	6.1 ± 0.1	14.1 ± 0.21	78.7 ± 0.26	1.60 ± 0.00	1.1 ± 0.1	44 ± 0	[12]
6	Dockounou-cake traditional	4.1 ± 0.1	1.3 ± 0.1	81.1 ± 0.4	9.4 ± 0.2	3.0 ± 0.2	79 ± 2	[13]
7	Optimized dockounou-cake (10 % maize flour)	4.1 ± 0.1	0.9 ± 0.1	82.4 ± 0.1	9.4 ± 0.2	3.1 ± 0.0	81 ± 1	[13]
8	Pounded plantain from afoto cultivar at "light green" stage of ripeness (stage 2)	6.1 ± 0.1	0.3 ± 0.1	91.0 ± 0.1	1.8 ± 0.0	0.8 ± 0.0	84 ± 4	[14]
9	Pounded plantain from afoto cultivar at "light green" stage of ripeness (stage 2) with okra sauce	13.6 ± 0.1	4.0 ± 0.2	77.6 ± 0.3	2.8 ± 0.0	2.0 ± 0.1	44 ± 2	[15]
10	Pounded plantain from afoto cultivar at "yellow with green tip" stage of ripeness (stage 5)	5.3 ± 0.1	1.3 ± 0.1	90.8 ± 0.1	1.9 ± 0.1	0.8 ± 0.0	85 ± 5	[14]
11	Pounded plantain from afoto cultivar at "yellow with green tip" stage of ripeness (stage 5) with okra sauce	13.0 ± 0.1	4.7 ± 0.3	77.6 ± 0.5	2.8 ± 0.1	2.0 ± 0.1	65 ± 3	[15]
12	Pounded plantain from agnrin cultivar at "more yellow than green" stage of ripeness (stage 4)	6.1 ± 0.0	0.5 ± 0.1	90.9 ± 0.0	1.77 ± 0.1	0.8 ± 0.0	80 ± 3	[15]
13	Pounded plantain from agnrin cultivar at "more yellow than green" stage of ripeness (stage 4) with okra sauce	13.5 ± 0.2	4.1 ± 0.3	77.6 ± 0.5	2.8 ± 0.1	2.0 ± 0.1	37 ± 1	[15]

Continued

14	Pounded plantain from agnrin at "green" stage of ripeness (stage 1)	3.50 ± 0.10	0.50 ± 0.00	94.1 ± 0.1	1.80 ± 0.00	0.20 ± 0.00	40 ± 1	[14]
15	Pounded plantain from agnrin at "green" stage of ripeness (stage 1) with okra sauce	11.77 ± 0.21	4.20 ± 0.26	79.57 ± 0.50	2.87 ± 0.1	1.63 ± 0.1	35 ± 4	[15]
16	Pounded plantain from ameletiha cultivar at maturity stage half-green, half yellow (stage 3)	10.5 ± 0.0	0.4 ± 0.1	86.77 ± 0.1	1.8 ± 0.0	0.5 ± 0.1	75 ± 2	[14]
17	Pounded plantain from ameletiha cultivar at maturity stage half-green, half yellow (stage 3) with okra sauce	16.53 ± 0.15	3.97 ± 0.23	74.93 ± 0.45	2.77 ± 0.1	1.80 ± 0.10	51 ± 3	[15]
18	Pounded plantain	5.4 ± 0.0	1.3 ± 0.0	80.9 ± 0.2	1.9 ± 0.0	0.6 ± 0.0	94 ± 4	[18]
	Cereals and by-products							
19	Rice	12.5 ± 0.2	0.7 ± 0.1	85.0 ± 0.2	0.3 ± 0.1	1.5 ± 0.1	54 ± 2	[16]
20	Rice with groundnut sauce	17.1 ± 0.1	24.5 ± 0.1	53.8 ± 0.2	2.1 ± 0.0	2.4 ± 0.2	45 ± 3	[17]
21	Rice with eggplant sauce (gnangnan)	13.6 ± 0.15	0.8 ± 0.1	80.2 ± 0.10	3.5 ± 0.1	2.0 ± 0.1	76 ± 1	[17]
22	Rice with palm nut sauce	11.7 ± 0.1	11.0 ± 0.1	73.0 ± 0.1	2.6 ± 0.0	1.7 ± 0.1	34 ± 1	[17]
23	Maize meal stiff porridge (cabatôh)	8.3 ± 0.4	0.8 ± 0.1	81.20 ± 0.70	5.5 ± 0.35	4.1 ± 0.50	75± 5	[18]
24	Maize meal stiff porridge or (cabatôh) with okra sauce	16.3 ± 0.4	5.0 ± 0.4	68.5 ± 1.01	5.6 ± 0.1	4.7 ± 0.50	57 ± 6	[15]
	Roots, tubers and by-products							
25	attieke agbodjama	0.9 ± 0.1	2.6 ± 0.1	94.7 ± 0.2	0.4 ± 0.0	1.5 ± 0.1	63 ± 2	[18]
26	attieke ayité	0.4 ± 0.0	1.6 ± 0.1	90.9 ± 0.2	5.6 ± 0.1	1.5 ± 0.0	88 ± 4	[15]
27	Pounded yam (Dioscorea cayenensis-rotundata; variety Kponan)	5.3 ± 0.1	2.6 ± 0.1	87.2 ± 0.2	2.1 ± 0.2	2.7 ± 0.1	85 ± 4	[18]
28	Pounded yam (Dioscorea cayenensis-rotundata; variety Kponan) with eggplant sauce (gnangnan)	11.2 ± 0.1	2.5 ± 0.0	68.3 ± 0.1	14.0 ± 0.1	4.0 ± 0.1	94 ± 1	[17]
29	Placali (a fermented cassava paste)	4.3 ± 0.3	0.0 ± 0.1	83.0 ± 0.4	8.4 ± 0.5	4.3 ± 0.1	106 ± 5	[18]
30	Placali with palm nut sauce	5.7 ± 0.2	31.1 ± 0.1	48.1 ± 0.2	11.5 ± 0.31	3.6 ± 0.1	86 ± 0	[17]

*Calculated by difference of moisture content, ash, fiber, lipids and protein. Ref.: reference; aloco aag6: fried plantain prepared from fruits at the full yellow stage; aloco aag7: fried plantain prepared from fruits at the full yellow with black spots; raf2: charcoal-roasted plantain prepared from fruits at the light green stage of maturity; Chips Cam1: plantain chips from the green stage; Klaclo kam8: fritters plantain from fruit at the black stage of maturity; GI = Glycemic Index; CHO = Carbohydrate.

2.2. *In Vivo* Glycemic Index Tests on Food Products

Six (6) studies, all approved by the Human Research Ethics Committee of Nangui ABROGOUA University, tested the 30 foods at a rate of 3 to 5 dishes per study protocol [12]-[18]. GI measurements were based on the FAO and WHO recommendations of 1998 [10] and the ISO 26642:2010 standard [19]. Oral hyperglycaemia tests were performed with these foods in the postprandial period (2 h) to determine the GI of the foods. The products tested were compared with a reference of 50 g of glucose, which was evaluated for each food. Portion sizes were calculated to provide 50 g of available carbohydrate. These tests were carried out on a cohort of people with normal blood glucose levels (4.5 - 5.5 mmol/L). In each study, healthy volunteers consumed all the products tested and the reference under fasting conditions, with at least one day's rest between two test days. The subjects tested the foods with a 250 ml glass of water. A fasting blood sample was taken (t = 0 min), followed by consumption of a test product. Postprandial blood glucose levels were measured for 120 min (15, 30, 45, 60, 90 and 120 min). Blood glucose concentrations were measured using glucometers (Accu-Chek Performa, Roche Diagnostic, Castle Hill, NSW, Australia). A total of 195 people (65 women and 130 men) were recruited in these six studies, with an age between 28 and 30 years (mean = 29.6, SD = 8.6) and a BMI between 20.05 and 21.2 kg/m^2 (mean = 22.0, SD = 2.2). GIs were determined using generally accepted equations [4].

$$GI = (\text{iAUC test food}/\text{iAUC reference food}) \times 100. \quad (1)$$

with iAUC: incremental area under the blood glucose curve.

2.3. Development of a Model to Predict GI

Database and selection of variables: Data from the food composition table and GI values of foods were selected for their high carbohydrate content (**Table 1**). The database contained GI values for each food for which the physico-chemical composition was known. The model developed included biochemical composition parameters that could be manipulated to simulate GI. Based on the literature consulted, a selection of these parameters was made to form a non-redundant subset that did not induce collinearity. In fact, some variables are considered correlated because they represent the same phenomena, such as pH and titratable acidity, or because they belong to the same group, such as total carbohydrates, sugars and starch, fibres, lignin and cellulose, ash and minerals, and reducing sugars, glucose and fructose. To avoid possible collinearities, only independent variables such as proteins, lipids, starch, cellulose, lignin, titratable acidity, etc. were preselected. The model developed therefore only took into account parameters that were relevant to the variable being modelled, *i.e.* these variables had to have a real influence on the GI value. Seven independent variables were selected and fed into an algorithm to develop the predictive model. These were water, protein, lipid, available carbohydrate, fibre, minerals and energy [4].

Artificial Neural Network Modeling: The neural network used in this study was a standard multilayer perceptron due to the simplicity of its learning algorithm and its ability to approximate and generalize [20]. It consists of an input layer, a hidden layer, and an output layer (**Figure 1**). The activation function on the hidden layer is a hyperbolic tangent function. The linear function was used as the activation function on the output layer. This architecture is based on an analysis of the coefficients of determination (R^2 close to unity) of the learning and test sets, then validation of this architecture using the statistical criterion of the mean square error (MSE) close to zero (0). A normalization, within an interval of [−1; 1], was first carried out on all the experimental data.

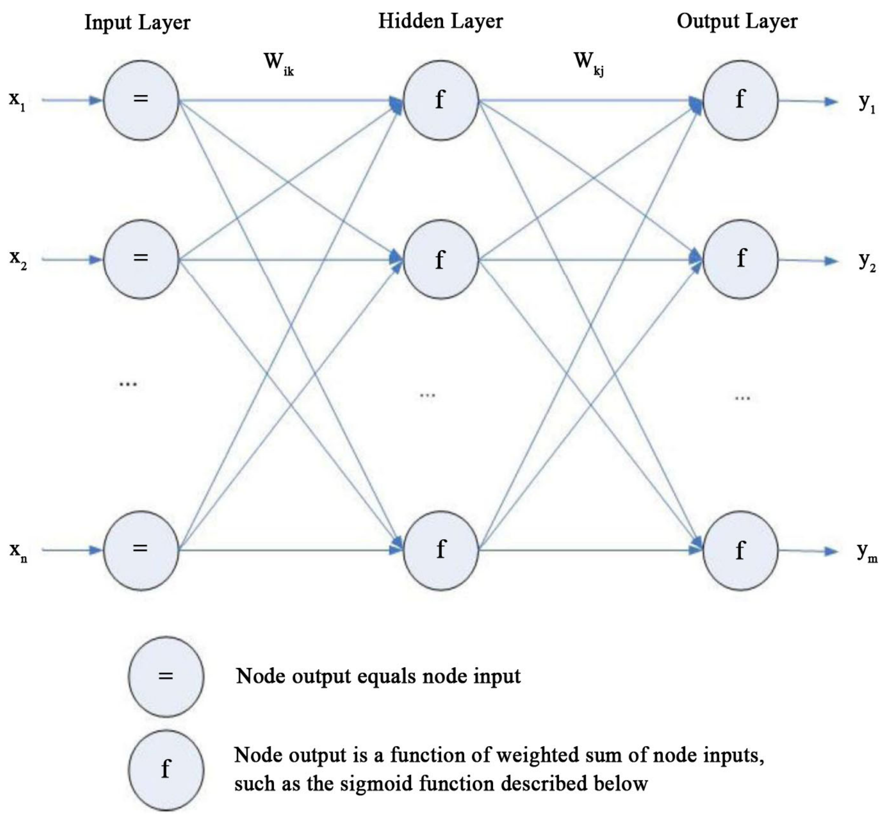

Figure 1. Architecture of a neural network [20].

Learning phase: In the development of a neural network, learning is the penultimate stage. The learning phase was supervised by the Levenberg-Marquardt algorithm [21] [22]. First, the optimal weights of the different connections are determined using a sample. The most commonly used method is backpropagation, where the optimal weights of the different links are first calculated using a sample [23]. At this stage, values are entered at the level of the input cells and the weights are corrected according to the error obtained at the output (the delta). This cycle is repeated until the error curve of the network becomes increasing [24]. The database, consisting of 7 variables and 53 observations, was used to build the neural network that would serve as the basis for learning, processing and validating the tests for the rest of the work. For this purpose, a computational program (algorithm) was designed and implemented in MatLab R2014a software (MathWorks Inc., Massachusetts, USA) to generate the structure of the neural network resulting from the linearization between the variables (water, proteins.... Xi) and the response (GI, Y). The diagram in **Figure 2** shows the algorithmic approach used. The algorithm used, including that for normalizing the raw data (Pre-processing of experimental data), is illustrated in **Figure 3**.

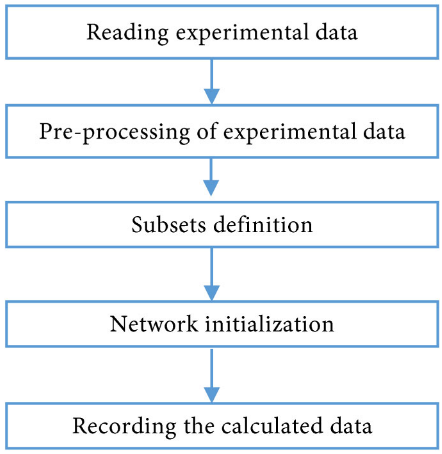

Figure 2. Algorithmic approach.

```
% Reading data
x=xlsread('ss.xlsx',-1);
y=xlsread('ss.xlsx',-1);
% Data pre-treatment
X=x';
Y=y';
ax=mapminmax(X);
ay=mapminmax(Y);
[L,C]=size(x);
% Subset definitions
iival=4:4:C;
iitst=2:4:C;
iitr=1:2:C;
p=ax(:,iitr);
t=ay(:,iitr);
v.P=ax(:,iival);
v.T=ay(:,iival);
tst.P=ax(:,iitst);
tst.T=ay(:,iitst);
% Network initialisation
for q=1:15 net=newff(p,t,q);
for i=1:500 net=init(net);
[net,tr]=train(net,p,t,[],[],v,[]);
at=sim(net,p);
for k=1:1 [m(k),b(k),r(k)]=pstrg(at(k,:),t(k,:));
A(i,k)=m(k);A(i,k+1)=b(k);A(i,k+2)=r(k);
end av=sim(net,v.P);
for k=1:1 [mv(k),bv(k),rv(k)]=pstrg(av(k,:),v.T(k,:));
A(i,k+3)=mv(k);A(i,k+4)=bv(k);A(i,k+5)=rv(k);
end at=sim(net,tst.P);
for k=1:1 [mt(k),bt(k),rt(k)]=pstrg(at(k,:),tst.T(k,:));
A(i,k+6)=mt(k);A(i,k+7)=bt(k);A(i,k+8)=rt(k);
end
% Recording calculated data
if ((i>=2) & (A(i,k+2)>=A(1:i-1,k+2))& (A(i,k+8)>=A(1:i-1,k+8)))
Pcc=[net.IW{1,1},net.b{1}]; Pcc2=[net.LW{2,1},net.b{2}];
xlswrite('poiddat.xls',Pcc,q,'A1');
xlswrite('poiddat.xls',Pcc2,q,'A50');
xlswrite('tempdat.xls', A(i,:),q,'A1');
Perf= [tr.perf;tr.vperf;tr.tperf];
```

Figure 3. Algorithm implemented in MatLab R2014a software.

Optimization and simulation of Artificial Neural Network: To obtain the best neuronal structure, the number of neurons on the hidden layer was optimized using probabilistic learning methods, particularly Bayesian. This optimization involved varying the number of neurons on the hidden layer from 1 to 15 [25]. For each neuronal structure, the calculations were repeated 1500 times. Next, the coefficient of determination (R^2) and root mean square error (RMSE) of each structure were determined. The best ANN was the one with the highest R^2, the lowest RMS, and the least complex topology. Once selected, the best ANN was used to simulate randomly selected trials. The quality of the simulation was assessed using the R^2 and the mean absolute error (MAE).

2.4. Model Estimation

As far as possible, the model developed had to incorporate these 7 explanatory parameters (input parameters) which could be influenced to modify the GI value of the foods consumed. The seven variables selected were used to select the most relevant variables for predicting GI, using MatLab R2014a software-defined at a significance level of 5%.

The general formula of ANN is as follows [26]:

$$Y = \sum \lambda_i^* y_i + b \tag{2}$$

with

Y: Value of the given GI, *i.e.* the response of the network.

λ_i: Weighting coefficients assigned to the hidden layer neurons

y_i: Summation of the values from the different activation functions

b: The bias is the error made by the network.

$$y_i = \mathrm{Tanh}(\sum x_i^* p_i + b_i) \tag{3}$$

with

Tanh: The hyperbolic tangent function is the activation or transfer function

x_i: The new transformed (normalized) values

p_i: The weight value of the element (observation) in the network, which is used to obtain the response given by the network

b_i: The bias, the error made by each neuron

B: The general bias of the ANN

For validation, the aim was to monitor changes in MSEs during model learning, testing, and validation. They should tend towards 0.

2.5. Evaluation of Neural Network Performance

The use of modelling for predictive purposes was to use mathematical approximation to identify the food composition parameters that influence GI. It was, therefore, possible to calculate the GI prediction ($\hat{G}$I), which are synthetic indicator of the estimated GI of carbohydrate foods, to analyze the similarities between ($\hat{G}$I) and (GI) and using the MatLab R2014a software.

3. Results

3.1. Artificial Neural Network Architecture

After creating the neural network and after several trials, the optimal neural architecture chosen consists of seven neurons in the input layer, nine neurons in the hidden layer, and one neuron in the output layer. The network architecture is shown in **Figure 4**. The input layer neurons represented the input variables. These were moisture content (X1), ash content (X2), crude fiber content (X3), protein content (X4), lipid content (X5), available carbohydrate content (X6), and energy value (X7). The number of neurons in the hidden layer varied between one and fifteen. The neuron in the output layer represented the output variable mean GI (Y).

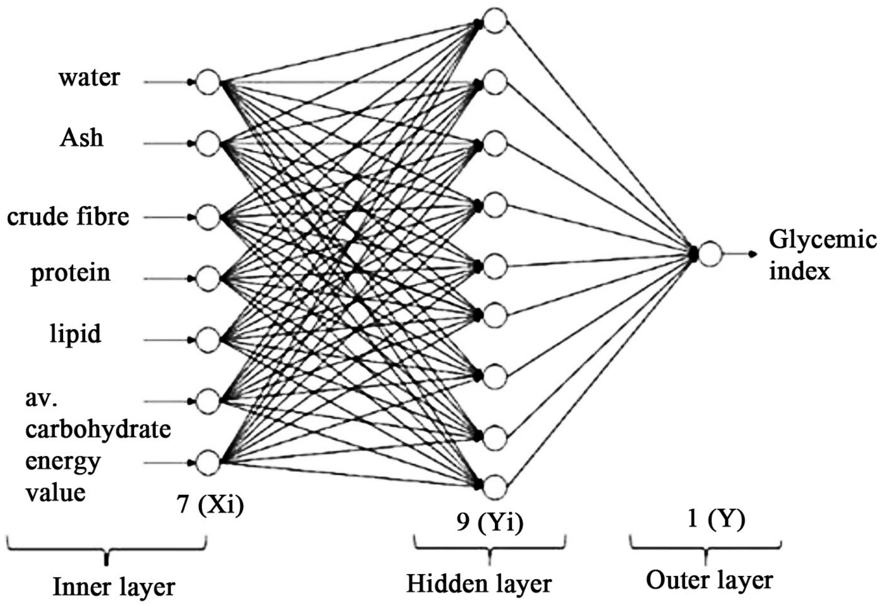

Figure 4. Architecture of the neural model selected (7:9:1).

3.2. Glycemic Index Predictive Model

Table 2 shows the performance of the best neural structures for each hidden neuron. The coefficient of determination R^2 varied between 0.853 and 0.973 during the learning phase. The 7-9-1 neural structure (7 neurons in the input layer, 9 neurons in the hidden layer, and 1 neuron in the output layer) showed the highest R^2 (0.968) during the test phase.

Table 2. ANN performance criteria for learning, testing and validation.

Numbers on the hidden layer	R^2 learning test	R^2 all test
1	0.853	0.801
2	0.890	0.863
3	0.916	0.912
4	0.956	0.958
5	0.961	0.957
6	0.956	0.946
7	0.950	0.945
8	0.958	0.946
9	0.973	0.968

Continued

10	0.963	0.952
11	0.942	0.906
12	0.961	0.956
13	0.954	0.946
14	0.965	0.957
15	0.950	0.936

The values of the weights and biases of this neural structure and the linear weighting values (λ_i) between the neurons from the hidden layer to the output layer are presented in **Table 3** and **Table 4**, respectively.

Table 3. Values of weights and biases on the ANN hidden layer (7:9:1).

Hidden Layer Neuron Number	weights							biases
	X1	X2	X3	X4	X5	X6	X7	
1	−0.857	1.148	0.751	0.378	0.084	0.902	0.057	1.812
2	−1.565	−1.053	−1.431	0.034	0.568	−1.280	−0.157	1.205
3	−1.118	0.755	−0.425	0.504	0.950	−0.054	−0.114	0.349
4	−0.381	−1.068	−0.140	−1.138	0.217	−0.380	−0.609	0.741
5	−0.513	0.746	−0.027	0.660	1.302	−0.353	1.335	−0.278
6	−0.748	−2.258	−0.601	−1.232	−0.948	1.615	0.104	0.723
7	0.969	−1.394	0.014	−1.274	−0.237	0.287	0.054	1.357
8	1.039	−0.915	−0.677	0.543	0.131	0.335	−0.986	1.427
9	−1.264	0.389	0.123	−0.752	−0.405	−0.923	0.926	−2.017

Table 4. Values of the weights and biases of the ANN output layer (7:9:1).

Neuron hidden layer	weights									biases
	y1	y2	y3	y4	y5	y6	y7	y8	y9	
Y	0.735	−0.203	−0.564	0.773	−0.079	−0.457	0.008	−0.210	0.643	−0.184

The linear model of this neural architecture (7:9:1) was as follows:

$$Y = 0.735y1 - 0.203y2 - 0.564y3 + 0.773y4 - 0.079y5 - 0.457y6 + 0.008y7 - 0.210y8 + 0.643y9 - 0.184 \quad (4)$$

3.3. Model Validation

Figure 5 shows the evolution of the Root Mean Squared Error (RMSE) as the network is trained. Learning stops when the validation RMSE reaches the threshold of 0.001. The weights and biases retained by the network are those that produce the lowest validation error. This minimum is reached after eight iterations, at the same time as the mean square error (MSE) during learning. All this confirms the effectiveness of the LM algorithm in guaranteeing a good MSE during learning and therefore a better generalization of the model.

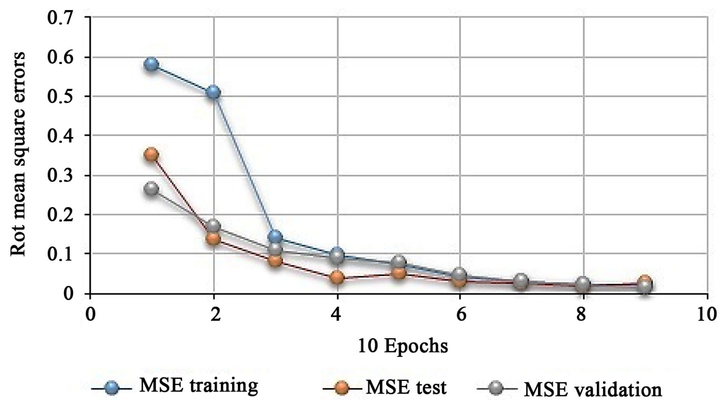

Figure 5. Evolution of root mean square errors.

The coefficient of determination R^2, which describes the closeness of the predicted value to the observed value according to the ANN model for the entire learning database, is shown in **Figure 6**. The graph shows a good correlation between the predicted value and the measured value, resulting in a coefficient of determination of 0.98212 (All: R = 0.98212; **Figure 6(D)**). **Figure 6(A)** shows the network trained with a regression coefficient of R = 0.9938 (Learning: R = 0.9938). The validation and test results also show a regression coefficient of R = 0.97786 and R = 0.96484 as shown in **Figure 6(B)** and **Figure 6(C)** respectively. Once the network had been trained, it was tested with different nutrient inputs. The results compare very well with actual glycemic index values.

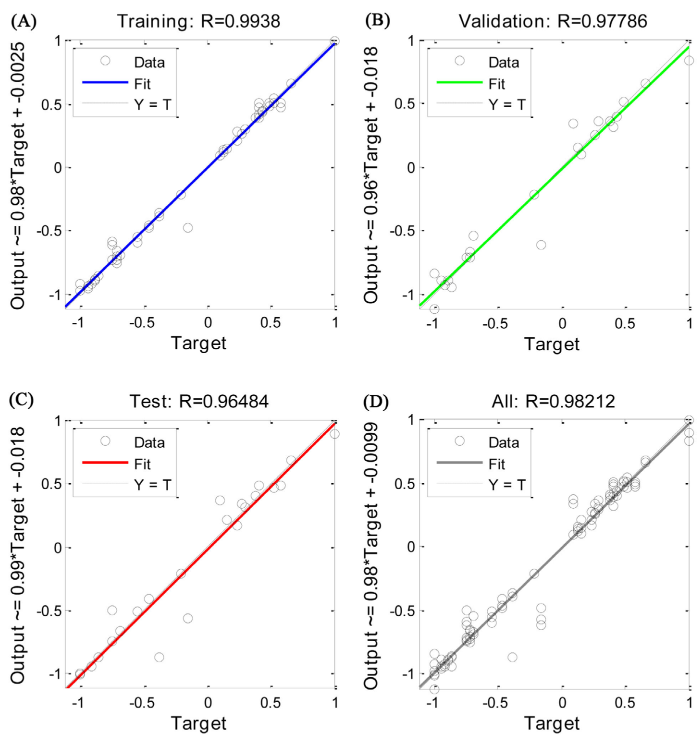

Figure 6. Adjustment lines during learning, testing, and validation of the artificial neural network.

4. Discussion

The use of modeling as a means of predicting GI is not new. This technique has been used in several studies [27]-[29], including those by Iancu *et al.* [8] and Pérez-Gandía *et al.* [9], where artificial neural networks (ANNs) were used as a modeling tool to predict blood glucose levels in an automatic insulin pump control system. The model defined in this study, which considers carbohydrate foods with or without sauce (non-carbohydrate food), was carried out in two stages. The first step was to determine the best neuronal structure capable of fitting the experimental data correctly, which resulted in 15 neuronal structures. These structures were analyzed using R^2 and RMSE. The second step was to use the selected artificial neural network as a prediction tool.

In the first stage, the performance of the best neural structures for each hidden neuron is shown. The R^2 coefficient varied during the learning phase from 0.853 to 0.973. This indicates a very good correlation between the values calculated by the neural structures and the experimental values in the learning database. Analysis of the mean square error of learning (MSE Learning) confirms this observation. Indeed, the Learning MSE tends towards 0. These values close to zero attest the good convergence observed between the calculated values and the experimental values, as in the study carried out by Nogbou *et al.* [30] on the drying kinetics of cocoa beans. On the other hand, the performances of the neural structures are significantly close overall. However, the 7-9-1 neural structure (7 neurons on the input layer, 9 neurons on the hidden layer, and one neuron on the output layer) shows the highest R^2 during the test phase ($R^2 = 0.968$), indicating a good predictive capacity of the method (ANN). It is therefore the most appropriate neural model. These results suggest that the ANN model selected has a good generalization capacity, *i.e.* it can provide a satisfactory response to an input that is not part of the data in the learning phase. This ability was previously demonstrated in the study by Magaletta *et al.* [31], which revealed a correlation coefficient $R^2 = 0.93$ for a range of little-studied foods. What's more, the prediction error is low, encouraging further research in this direction.

The use of artificial neural network modeling to predict the GI of foods is not widespread. However, this model is a tool that would make it possible to avoid tedious calculations to estimate the GI of foods based on their physico-chemical composition. It is also original in that several attempts have been made in this direction, either to predict GI. Most predictive trials have been based on the in vitro digestibility of carbohydrate feeds but have been hampered by the fact that this digestibility does not consider important physiological aspects of digestion. Factors such as gastric emptying [32], insulin response [33] or the effect of food chewing [34], which have a major influence on GR and GI, have not been considered. On the basis of the seven variables selected, the model developed is overall significant. These variables adequately explain the GI. Some of these variables have little influence on the GI, while others have a much greater influence. The model shows that the water, fat, protein, carbohydrate, mineral and calorie content have a significant influence on the GI of these traditional dishes. When giving out dietary advice, using the glycemic index will most likely account for a high degree of variability, especially in environments like Cote d'Ivoire, where the majority of foods eaten consist of mixed meals.

5. Conclusion

A model for predicting the glycemic index using ANN was developed to predict the experimental glycemic index. The ANN was shown to be able to predict the glycemic index with a high degree of accuracy. This work demonstrated the advantages of using ANN as a predictive tool. The simulation results are presented in terms of the root mean square of the residual error and the linear correlation coefficient between the measurement and the predicted values. Taken together, these results suggest that the proposed method can be used to estimate the glycemic index of mixed meals. Neural networks have demonstrated a high capacity for learning and prediction. The proposed model paves the way for future work aimed at anticipating the potential impact of these foods on people's health more easily and at lower cost.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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